DEVELOPMENT AND TESTING OF FUEL LOADINGS, DISTURBANCE AND FIRE SPREAD MODELS BASED ON STAELLITE IMAGERY AND FIELD SURVEYS

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ABSTRACT

In this study, we developed a series of models to assess fire threat across a landscape to inform managers responsible for mitigating this threat. Effective implementation of hazard fuels reduction treatments requires site-specific information of fuel loadings, stand structure and topography at a fine resolution. Spatially explicit analysis of current fuel conditions, fuel generating agents and the impacts of various treatments on predicted fire behavior would allow the managers to position treatments where they would be more beneficial. This type of information would also facilitate the modification of treatment options to maximize effectiveness. Given the high cost of fuels treatments, the ability to tailor treatments for maximum benefit and cost-effectiveness would be advantageous to the managers.

INTRODUCTION

Wildfires are an increasing problem in the west because of increasing fuel loadings during a period of fire suppression. A very destructive fire season involving a number of extremely large wildfires occurred in the Intermountain West during the year 2000 (Borig and Feguson 2002). Because of the accumulation of fuels many of these fires were more intense and severe compared to fires in past years.

Lightning is a natural cause of wildfires ignition. In the Intermountain West, lightning accounts for a high proportion of forest fires that cause substantial damage. Efforts are under way in the forest fire research community to better understand the relationship between lightning and fire ignition. Statistical models such as those based on regression or generalized linear models are being applied to data of lightning and fire ignition. Spatially explicit, empirically derived models of ignition probabilities are critical to understanding the behavior of future fires and for evaluating the effects fuels management activities on fire hazard. Developing spatially explicit fire ignition models have generally been difficult to generalize in spatial models of fire spread such as FARSITE and other landscape type models. To overcome this, abstraction or extrapolations are used as substitutes for empirically derived ignition probabilities.

Wildfire behavior in forests depends on characteristics of fuels, weather, and topography. Little can be done to manipulate and manage weather and topography. Most pre-suppression efforts aimed at managing wildfires involve manipulating fuels. Spatial properties of the composition, quantity, size, compactness, and arrangement of fuels are major factors that determine initiation, intensity, and spread of forest wildfires (Pyne et al. 1996). Many processes affect fire hazard by influencing and changing fuel conditions. In the past, the emphasis has been on eliminating disturbances, thus allowing forest stands to get abnormally dense. Much emphasis on fire hazard reduction has been on cutting and removing trees. An alternative is the purposeful uses of natural disturbances, like diseases, and others. Disturbance management is an emerging field, yet the tools for managing disturbances aimed at mediating wildfire risk and improving forest health is limited.

Fuel management methods include: reducing fuels, redistributing fuels, removing fuels, changing the flammability characteristics of fuels, and breaking up fuel continuity (Omni 1996). These management methods are based on existing fuels, not the agents or the ecological processes that create these fuels. Fire, decomposition and decay are natural processes that reduce fuels. Diseases, insects, strong wind events, and other small scale abiotic and abiotic disturbances create fuels. Fuel management aims at balancing the fuel reduction processes with the fuel generating processes. Existing fuel management methods are largely short term, because they focus on the symptoms of fuel accumulation, not the processes underlying fuel retention and generation.

Manipulating (mediating or enhancing) forest diseases and other fuel-generating disturbances could be a useful long-term strategy for managing fire risk, but the integrated models needed to characterize and predict the influence of these disturbances on fire behavior, and to guide disturbance management activities are lacking. Landscape models of fuel and fuel-generating disturbances distributions would be an important decision support tool to help managers develop prescriptions for mediating fire risk by managing spatial patterns of fuel-generating-agents. Managers would use these maps to: 1) select and prioritize prescriptive fuels/disturbance management activities aimed at controlling fire risks, and determine where to do them; 2) monitor fuel abundance and

distribution at mid- and landscape-scales; 3) predict how fire would spread with changing conditions in the landscape.

Forest managers have utilized models to aid in predicting fire behavior and to map varying fire spread scenarios during a given time period. FARSITE (Finney 1998), BEHAVE (Andrews 1986) and other fire behavior and growth decision support systems are based on a mathematical model for quantifying fire spread in surface fuels developed by Rothermel (1972). This model is composed of a series of calculations for heat required for ignition, propagating flux, reaction intensity, and effect of wind and slope. Weather and fuel parameters are used as input for these calculations. Spatial properties of the composition, quantity, size, compactness, and arrangement of fuels are major factors that determine initiation, intensity, and spread of forest wildfires (Pyne *et al.* 1996). Wildfire fuels are commonly split into three classes: aerial fuels, ground fuels, and surface fuels. Of these, surface fuels have the greatest influence on fire behavior. Surface fuels include trees less than 1.8 *m* tall, shrubs, grasses and forbs, litter, and coarse woody debris (Pyne *et al.* 1996). Small-scale disturbances alter abundance and composition of the standing dead tree and coarse woody debris components of surface fuels (Lundquist and Beatty 2002).

Recent research in generating prediction maps for various disturbance agents using remotely sensed imagery based hold promise for describing the spatial distribution and extent of various disturbance agents. Lundquist and Reich (2006) in the Black Hills of South Dakota have shown that the spatial distributions and severity predictions can be accomplished remotely with minimal errors. Distribution maps of bark beetles, root diseases, stem cankers, stem rots, and wind damage were generated using binary regression trees to describe presence/absence of each agent and the resulting surfaces were subjected to kernel estimator to determine intensity or number of pixels per hectare that one would expect to observe a particular causal agent (Figure 1).

In this study we develop a spatial point process model of lightning fires and integrate this within the family of fire spread models to examine the relationship between the spatial distribution of lightning fires, precipitation, fuel loadings and continuity of fuels to develop a system for selecting and prioritize prescriptive fuels management activities aimed at controlling fire risks, and determine where to do them.

MATERIAL AND METHODS

Study Site

This study was conducted in the Black Hills National Forest in west central South Dakota, USA. The Black Hills are the easternmost outlier of the Rocky Mountains and covers approximately 650,000 *ha*. Elevation reaches 2300 *m* (Froiland 1990). Forests occur between 966 *m* and 2175 *m* (Figure 2). Precipitation averages about 750 *mm* per year, mostly as rain during summer months. *Pinus ponderosa* Douglas ex P. Laws is the dominant tree species. At the higher elevations, *Picea glauca* (Moench) Voss is the dominant tree species, while both *Populus tremuloides* Michx., and *Quercus macrocarpa* Michx. (Hoffman and Alexander 1987) dominate in the northern part of the forest.

Lightning Data

Historical fire data (N = 4669) was acquired from the Black Hills National Forest covering the period from 1970 to 2003. Seventy-one percent (N = 3231) of the fires were caused by lightning, and 64 percent of the lightning fires occurred in the study area (N = 2072). Visual observation of the spatial distribution of lightning fires overlaid upon a digital terrain model indicated a strong relationship between the frequency of lightning fires and elevation.

Precipitation Data

Monthly precipitation data was acquired from the High Plains Regional Climate Center, University of Nebraska, Lincoln. Fourteen weather stations (Bear Ridge, Custer, Deadwood 1 and 2, Edgemont, Hermosa, Hot Springs, Johnson Siding, Lead, Medicine Mountain Mount Rushmore, Rockford, Spearfish, and Wind Cave) were selected to represent precipitation patterns in the Black Hills National Forest. The historical precipitation data covered the period from 1961 to 2004. Statistical analysis was performed to determine the relationship between precipitation and lightning fires using regression analysis.

Modeling the Spatial Distribution of Lightning Fires

The spatial relation between lightning fires and elevation was modeled using minimum threshold theory (Reich *et al.* 2000). Individual lightning fires were assumed to have a threshold such that any increase in elevation would be considered a rare event to observe a lightning fire. Since is was only possible to observe the location of individual lightning fire, and not lightning strikes, it was not possible to find the actual relationship between lightning fires and elevation. Thus, it was determined whether or not this threshold was above or below a particular elevation. This information was used to develop a probability model describing the relationship between the presence of a lightning fire and elevation using a logistic regression model. The logistic response function was assumed to be an appropriate descriptor of the relationship between lightning fires and elevation and the probability that a lightning fires would be observed.

Using an algorithm developed by Reich *et al.* (2000) we developed a spatial model combining the threshold model with a digital elevation model for the Black Hills National Forest. In simulating the spatial pattern of lightning fires, we assumed there were no interactions between individual fires. The k-function (Ripley 1981) was used to test the null hypothesis that the spatial distribution of lightning fires is dependent on the spatial distribution of elevation in the Black Hills National Forest. The goodness-of-fit of the point process models were assessed using a Monte Carlo simulation to create simulation envelopes for the k-function, corrected for the edge effect. This allowed comparison of the empirical k-function (observed spatial distribution of lightning fires) to that of the point process model.

Forest Fuel Models

Field Sampling for Fuel Loading. Each vegetation type was stratified into broad forest classes (pine, spruce, oak, aspen, mixed conifer, pinyon-juniper, and meadows) based on an existing vegetation map. Variability of each stratum was determined using an initial sample of 50 plots in each forest; remaining sample plots were allocated proportional to the variability observed in forest structure and fuel loadings. Using a stratified sampling design, 151 and 85-30 *m* x 30 *m* randomly located sample plots were georeferenced in the Black Hills and Lincoln National Forest, respectively.

A 42 *m* transect was established diagonally across the sample plots. Three 1 *m* transects were established 7 *m*, 21 *m,* and 35 *m* along the 42 *m* transect. We used planar intersect sampling (Brown et al. 1982) to estimate fuel loadings in tons/ha for the following size classes: < 0.6 cm; 0.6 cm to 2.5 cm; 2.5 cm to 7.6 cm; and 7.6 + cm sound and dead. Fuel loadings in size classes under 7.6 cm were estimated by counting the number of intercepts on the three 1 m transects by species group. Fuel loadings for woody material greater than 7.6 cm were estimated by measuring the diameter of all intercepts on the 42 m transect, by species group. Data were also collected on the depth (cm) of the litter and duff on the three 1 m transects, along with estimates of the height of the woody fuels (cm) above the forest floor. All fuel loading estimates were adjusted for slope and species group. Data collected included: average tree height (*m*), height to the base of the live crown (*m*), canopy closure (%), average height (*m*), diameter (*m*), and number of shrubs per *ha*, and total tree basal area (m^2/ha). Information on shrubs was used to estimate shrub volumes per *ha,* which included air space. Fuel loadings were calculated using procedures developed by Brown *et al.* (1982).

Modeling forest fuels. Modeling of forest fuels was accomplished in two stages (Reich *et al.* 2004). In the first stage, multiple regression analysis was used to explore the coarse-scale variability in forest fuels as a function of elevation, slope, aspect, and Landsat TM bands. To account for differences among forest classes, dummy variables were introduced to the models as interactions with elevation, slope, aspect, landform, and the eight Landsat bands. For each component of forest fuels modeled, we used a stepwise procedure to identify the best subset of independent variables to include in the regression models.

Error (i.e., residuals) associated with the TS models was modeled using binary regression trees (RT). The RT is a non-parametric approach to regression that compares all possible splits among the independent (continuous) variables using a binary partitioning algorithm that maximizes the dissimilarities among groups. Once the algorithm partitions the data into new subsets, new relationships are developed, assessed, and split into new subsets. The algorithm recursively splits the data in each subset until either the subset is homogeneous or the subset contains too few observations (e.g., < 5) to

be split further. Interpolation using RTs is relatively insensitive to sparse data. Independent variables considered in the RT included elevation, slope, aspect, landform, Landsat TM bands, and forest class, the latter being treated as a categorical variable. To avoid over-fitting the models, a 10-fold cross-validation procedure (Efron and Tibshirani 1993) was used to identify the tree size that minimizes the total deviance associated with the trees.

Grids representing the various forest fuel components were generated for the best fitting TS model using the model's parameter estimates. Similarly, grids representing the error in each TS model were generated by passing each grid for the appropriate independent variable through the RTs. The final predicted surfaces of the different components forest fuels were obtained from the sum of the TS and RT grids.

Semi-variograms were used to evaluate spatial dependencies among the residuals from the various forest fuel models. If the residuals exhibited spatial dependencies, generalized least squares (GLS) was used to estimates the regression coefficients associated with the TS model (Upton and Fingleton 1985).

The effectiveness of the final models was evaluated using a goodness-of-prediction statistic (G) (Agterberg 1984; Kravchenka and Bullock 1999; Guisan and Zimmermann 2000; Schloeder *et al.* 2001). The G-value measures how effective a prediction might be relative to that which could have been derived by using the sample mean (Agterberg 1984):

$$G = \left(1 - \left\{\sum_{i=1}^{n}\left[Z_i - \hat{Z}_i\right]^2 \Big/ \sum_{i=1}^{n}\left[Z_i - \overline{Z}\right]^2\right\}\right),$$

where Z_i is the observed value of the i^{th} observation, $\hat{Z}_i$ is the predicted value of the i^{th} observation, and $\overline{Z}$ is the sample mean. A *G*-value equal to 1 indicates perfect prediction, a positive value indicates a more reliable model than if one had used the sample mean, a negative value indicates a less reliable model than if one had used the sample mean, and a value of zero indicates that the sample mean should be used to estimate Z. Error associated with fuel models was estimated using procedures described in Reich et al. (2004).

Custom Fuel Models

A *k*-means clustering algorithm was used to partition the sample data of fuel loadings into three groups to minimize the within group sum of squares (Hartigan and Wong 1979). Variables used in the analysis included the < 0.6 *cm*; 0.6 *cm* to 2.5 *cm*; 2.5 *cm* to 7.6 *cm* fuel loadings, fuel height and shrub volume. The first three variables are important components required to define custom fuel models in FARSITE. The clustering algorithm was then used generate a GIS grid of the Black Hills where each forested pixels were assigned to one of the three fuel classes.

Fire Hazard

FlamMap fire behavior program was used to develop estimates of fire behavior. FlamMap is a simplified version of the FARSITE fire modeling program (Finney 1998). The distinction between the two is that FlamMap does not track fire behavior over time, but instead presents fire behavior under fixed set of weather conditions and produces outputs that assume an entire landscape is burning. FlamMap uses the following spatial data: elevation, slope, aspect, crown base height, crown bulk density, canopy cover, as well as custom fuel models. FlamMap also required input and wind data and fuel moisture content. Weather data was obtained from the Black Hills for the month of August. We assumed a 30 mph winds from the northwest which represents the prevailing wind direction. In estimating fuel moisture we assumed drought conditions.

The fuel models and other appropriate spatial layers were modified to simulate a 10%, 30%, 50% and 70% reduction in fuel loadings throughout the forest. FlamMap was used to generate a spatial layer of fireline intensity associated with each of the four levels of treatment as well as for the current conditions (i.e., no treatment). Monte Carlo procedures were used to simulate the spatial distribution of 1000 lightning fires ranging in size from 1 acre to 5000 acres (Table 1). Only 900 fires were simulated for the largest fires. For simplicity, it was assumed that the fires were circular in shape. For each fire, the fireline intensity was recorded for each 30 *m* x 30 *m* pixel associated with a fire. Summary statistics were computed for each treatment and fire size was used to evaluate the influence of fuels treatments on reducing fire hazard.

RESULTS

Description of the Fire Data

Figure 2 depicts the spatial location of all fires during the period from 1970 to 2003. The fires are overlaid on the digital elevation model for the Black Hills. Sixty-nine percent of all fires occurred in the study area. Lightning (64%) was the major cause of fires in the Black Hills (Figure 3). Cooking was the next major cause which accounted for 13% of all fires. All other causes had frequency of occurrences less than 5%. There was no significant difference between the distribution of fire causes for the complete data set and the subset of fires that occurred in the study area. Fires occurred throughout the month period in any given year with the highest frequency in the summer months (Figure 4). Lightning fires were limited to an eight month period between March and October with July (35 %) and August (30 %) having the highest frequency of lightning fires. The number of lightning fires in a given year ranged from a low of 20 to a high of 150 (Figure 5). Most lightning fires (94%) were less than two acres in size (Figure 6). There were only two lightning fires that exceeded 5000 acres in size.

Predicting the Number of Fires

Regression analysis was used to develop a model to predict the total number of lightning fires in an eight month period as a function of the total amount of precipitation in the same period of time. The final equation is given by:

$$\hat{L} = 403.4346 - 31.0421 * P + 0.655189 * P^2$$
$$R^2 = 0.51,\ n = 34,\ s_{xy} = 25.08$$

where $\hat{L}$ is the predicted number of lightning fires in the eight month period from March to October, and P is the total precipitation (*in*) expected during the same eight month period. The number of lightning fires decreased with increasing precipitation (Figure 7). This suggests that dry thunder storms have a higher probability of starting a lightning fire. Given that one can predict the total number of lightning fires in a given year, the empirical distribution function of the number of fires in a given month (Figure 4) could be used to allocate lightning fires to individual months within a given year.

Probability of Lightning Fires

A general linear model with a logistic link was used to model the probability of observing a lightning fire as a function of elevation. The estimated probability density function (*pdf*) of the thresholds of elevation is depicted in Figure 8. Elevations between 1500 *m* and 2000 *m* have the highest probability of a lightning fire. The probability of a lightning fire decreases at the lower and higher elevations in the Black Hills. This *pdf* was used to generate a GIS surface of the probability of observing a lightning fire (Figure 9). The pdf was rescaled by dividing by the maximum probability to facilitate the simulation of the spatial distribution of lightning fires in the Black Hills National Forest.

Simulating the Spatial Distribution of Lightning Fires.

To simulate the spatial distribution of lightning fires we condition on the total number of lightning fires. A set of random *x, y*-coordinates are generated and the probability of observing a lightning fire is observed. A uniform random number over the interval [0, 1] is generated. If the random number is less that the probability of observing a lightning fire the location of the fire is accepted. If not, the process is repeated. This procedure is continued until all of the lightning fires have been assigned a geographical location. The point process model was evaluated using a transformed *k*-function. The empirical k-function was contained within the bounds of the simulation envelopes suggesting the point process model adequately described the spatial relationship between lightning fires and elevation. Since it was not possible to express the lightning model mathematically in the form of the k-function it was not possible to assess the goodness-of-fit using an exact test such as the Cramer-von-Mises statistic (Cressie 1991). Thus, we must rely on graphical procedures to assess the goodness-of-fit of the point process model.

Forest Fuel Models

Tables 2 through 5 summarize the predictive performance of the fuel models developed for the Black Hills National Forest.

The majority of the sample distributions of forest fuels on the Black Hills National Forest were highly skewed to the right, which influenced the final fit of the

models. It was not possible to transform the data to sufficiently remove this skewness. However, residuals plots, and plots of predicted vs. observed fuel values did not show any trends to suggest a systematic bias in any of the models.

Table 2 summarizes the independent variables used to describe the coarse-scale variability in fuel loadings. Fuel loadings were linearly correlated with the topographic and Landsat TM data, and these linear relationships varied significantly among forest type. Not all of the Landsat TM bands and none of the forest class variables (Tables 4) were used in regression trees to describe the error in the regression models for the Black Hills (Table 5). This suggests that the regression models for the various fuel components accounted for all the structural variability due to species composition. The tree sizes selected to minimize the total deviance in the regression trees ranged from 23 to 49 splits.

The overall contribution of the models (Table 4) in describing forest fuels varied with the model. Overall model performance ranged from a low of 0.55 for the 0 *cm* - 0.6 *cm* fuels of to a high of 0.71 for the 2.5 *cm*– 7.6 *cm* fuels. The remaining models had G-values ranging from 0.61 to 0.69 for the Black Hills.

Prediction bias was nominal (Table 5) for all models. Minimum, maximum, and quartile values showed that estimated and observed value distributions were similar for all models. Estimation errors for the depth of the duff and litter had a similar spread in the estimation errors. In terms of the fuel models, the 2.5 *cm* – 7.6 *cm*, < 7.6 *cm* and > 7.6 *cm* fuel models had the largest spread in terms of the estimation errors, while the < 0.6 *cm* fuel model had the least spread. The mean estimation errors did not differ significantly from zero (p-value $\geq$ 0.050). The MAE was smaller than the RMSE for all models indicating that in general, the models are more accurate in predicting regional or global means than on a point-by-point basis.

SMSE results (Tables 5) showed that the computed EEVs were statistically consistent with the true errors for all models, as they were within the interval [0.72 - 1.28] (Hevesi *et al.* 1992). This suggests that EEVs could be used to assess estimates of uncertainty for new observations. The 0.95 confidence coverage rates ranged from a low of 0.90 for the 2.5 *cm* - 7.6 *cm* fuel model to a high of 0.99 for the litter model. Only seven of the model had coverage rates less than 0.95, the lowest being 0.90 for the 2.5 *cm* – 7.6

cm fuels. This suggests that confidence intervals constructed using the EEV for these fuel models may not be large enough to insure a 95% confidence interval around our estimates.

Custom Fuel Models

To better reflect fire behavior models such as FARSITE and FlamMap allow the user to define custom fuel models. Important components required to define such models include the < 0.6 *cm*, 0.6 *cm* to 2.5 *cm*, and 2.5 *cm* to 7.6 *cm* fuel loadings, which were modeled by Reich *et al.* (2004). Using these variables and information on shrub volumes and fuel height, a *k*-means clustering algorithm was used to partition the sample data of fuel loadings into three groups to minimize the within group sum of squares (Hartigan and Wong 1979). Table 6 summarizes the within group statistics of the variables used in the clustering. The fuel classes were numbered 20, 21 and 22, respectively. Figure 10 depicts the spatial distribution of the three fuel classes for the Black Hills National Forest. Fuel class 21 covers approximately 89% of the forested area and is characterized by relatively low fuels. Fuel class 20 covers about 10% of the forested area tends to have a higher fuel loading in the 2.5 *cm* to 7.6 *cm* class and slightly higher volume of shrubs as compared to fuel class 21. Fuel class 22 covers only 1% of the area, but tends to have the highest amounts of fuel. To be able to use these fuel classes in the program FARSITE, we would also need to obtain information on the area-to-volume ratio of fuels which was not collected at the time of this study. This information could have been collected, along with other required information and modeled using the procedures described by Reich et al. (2004). GIS grids for canopy closure (required by FlamMap), average tree height, height to the base of the live crown were also modeled and used as input to FlamMap to better describe forest conditions.

Fireline Intensity

FlamMap was used to generate a grid surface of fire-line intensity based on the current conditions in the Black Hills (Figure 11). Fireline intensity values are useful in determining extreme fire hazard areas. Each pixel was assigned to one of three classes: less than 100 BTU/ft/sec (low rating), 101-399 BTU/ft/sec (moderate rating), and 400 BTU/ft/sec and over (extreme rating). Based on current conditions, 29% (385,683 acres)

of the forest has a low rating, 69% (919,517 acres) a moderate rating and 2% (22,960 acres) an extreme rating. Areas with a low rating were located in the higher elevations outside the zone of high probability of lightning fires and in the southern part of the forest which isdominated by grasslands. This area also has a low probability of a lighting fire.

Influence of Fuel Treatment Programs on Fire Hazard

Table 7 summarizes the variability in fireline intensity for lightning fires of different sizes and levels of fuels treatment. Under current conditions, the average fireline intensity associated with potential lightning fires is 155 BTU/ft/sec. Reduction in fuel loadings brings about a similar reduction in fireline intensity. A 10% reduction in fuel loadings resulted in an average reduction in fireline intensity of 17% to 128 BTU/ft/sec. In contrast, a 70% reduction in fuel loadings resulted in an estimated 79% decrease in fireline intensity to 38 BTU/ft/sec. The variability in fireline intensity increased with fire size (Figure 12). The highest variability is associated with the current conditions. This variability decreased with higher levels of fuel treatment. For fuels treatments of 50% and 70% there was no consistent relationship between the observed variability in fireline intensity and fire size.

DISCUSSION

Lightning fires in the Black Hills National Forest have a unique spatial and temporal pattern in relation to elevation. The ecological role of fire is a manifestation of these patterns. Minimum threshold theory was used to investigate the spatial relationship between lightning fires and elevation. The results suggest that lightning caused fires occurred at mid-level elevations when compared to the distribution of elevations in the study area. Relative high fire frequencies at mid-level elevations are commonly reported in the literature (Barten 1994, Granstrom 1993, Marsden 1982). Barten (1994) showed that the lowest and highest elevations forests in the southern Rocky Mountains are fuel and moisture limited, thus lowering fire frequencies. Elevations where fire frequencies are highest are characterized by conditions that are dry and fuels are continuous enough to facilitate fire ignition and spread. By evaluating fire-elevation interactions we hope to provide an easily repeatable standardized process for developing ignition probability

surfaces using relatively easily obtainable geospatial data representing lightning fire data and topographic data. This model coupled with empirical data allows one to simulate the spatial distribution of lightning fires in the Black Hills given an estimate of the level of precipitation expected during the fire season..

The models of forest fuels can be very useful in that they provide detailed estimates of the structural components of forest fuels at a fine-scale (30 *m* resolution) with relatively high accuracy. These models, in general, produce greater accuracy and spatial resolution than traditional techniques based primarily on remotely sensed data, such as Landsat TM data, which are limited to what the sensors can directly detect. The results are also superior to traditional methods of mapping forest fuels in that they are generally insufficient at predicting the spatial variability in forest fuels within a given stand.

The models describe 0.55 (0 – 0.6 *cm* fuels) to 71% (2.5 – 7.6 *cm* fuels) of the spatial variability in the components of forest fuels observed on the field plots. The poor ability of some of the models to describe the various components of forest fuels may be due, in part, to certain types of management activities on the forest, such as controlled burning and thinning. The models assume that similar forest stands have similar characteristics with respect to forest fuels. It may be possible to include past management activities in the models to account for this variability and to improve the overall accuracy of the models. All models provided unbiased (p-value > 0.05) or marginally biased estimates of forest fuels. In the latter models, the bias was not large enough to limit the use of the models for predictive purposes.

Results of the 10-fold cross-validation indicated that the estimated error variances for the models provided statistically consistent estimate of the true prediction errors associated with the models. These results suggest that the estimated error variances could be used to assess estimates of uncertainty when the models are applied to non-sampled plot locations.

The fuel models were used to calibrate FlamMap to represent current fuel conditions in the Black Hills National Forest. Coupled with the spatial model of lightning fires in the Black Hills, FlamMap was used to simulate lightning fires of various sizes under

different levels of fuels treatments. This facilitates the comparison of pre and post treatment effectiveness and for identifying hazardous fuel and topography combinations thus aiding in positioning treatments where they would be most beneficial (Straton 2004). Output from FlamMap can be combined with the probability of an lightning fires to develop a GIS coverage of wildfire susceptibility.

In this study, a method of modeling the spatial distribution of lightning fires and forest fuel loading was developed based on satellite imagery, field plots and predictive spatial fuel models. Various types of disturbances kill or damage trees in different ways that influence the probable occurrence and spread of wildfires. These disturbances directly impact wildfires by producing fuel that burns. They indirectly influence fires by creating corridors of fire spread by the spatial patterns that they create across the landscape. Managing fire hazard by manipulating spatial patterns of fuels is the basis of spatial management. Decision support tools like the distribution models developed here greatly simplify decision making tasks about various disturbances. The methods and models developed in this study could be useful for fuel management, pest management, forest planning and forest health projects.

Distribution models like those developed here greatly add to assessments of the relative importance of various types of disturbances and in doing so, offer arguments for which disturbances should or should not be managed, and which disturbances impact forest health. They offer a useful guide to the options available to managers, and for choosing among options. They also offer a means of facilitating consensus among conflicting stakeholders over threats and opportunities presented by patterns of hazards due to various disturbances across the landscape.

Fuel management tools for various types of disturbances have mostly been developed for stand scale operations. Few management tools have been designed for landscape scale decision making. These tools would include not only what preventive, suppressive, and/or restorative activities could be done, but where these activities should be done; especially when resources are limited and choices need to be made about where existing resources should be committed. Distribution maps like those generated in this study help in developing management strategies for short and long-term mediation of fire hazard at landscape scales.

Abnormal fuel loads are symptomatic of a disturbed landscape. Fuel management activities are largely aimed at mediating symptoms of fire risk and hazard, not the causes. Focusing on manipulating existing fuels is arguably a short term solution. A longer term solution would be to manage the disturbance sources of these fuels. The long term goals of this study are to develop techniques for assessing fire risk based on predictions of spatial distribution and spread of fuel-generating-diseases at landscape scales; using these predictions as a basis for monitoring changing fuel conditions associated with diseases; integrating these models into established fire behavior models to predict the effects of various disease management activities aimed at mediating fire risk by managing diseases.

SUMMARY

In this study, we developed a series of models to assess fire threat across a landscape to inform managers responsible for mitigating this threat. Effective implementation of hazard fuels reduction treatments requires site-specific information of fuel loadings, stand structure and topography at a fine resolution. Spatially explicit analysis of current fuel conditions and the impacts of various treatments on predicted fire behavior would allow the managers to position treatments where they would be more beneficial. This type of information would also facilitate the modification of treatment options to maximize effectiveness. Given the high cost of fuels treatments, the ability to tailor treatments for maximum benefit and cost-effectiveness would be advantageous to the managers.

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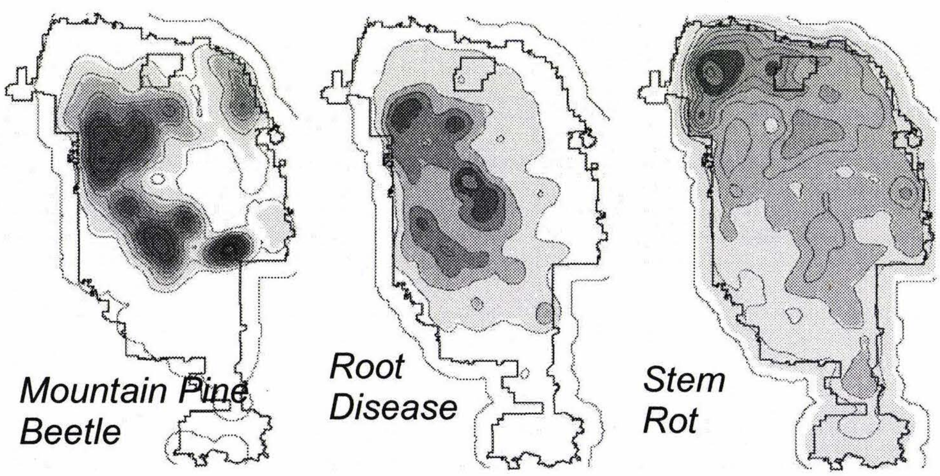

Figure 1. Spatial distribution and intensity (number of 30 m pixels per hectare) of mountain pine beetle, Amillaria root disease and stem rot on the Black Hills Nation Forest, South Dakota (Lundquist and Reich 2006).

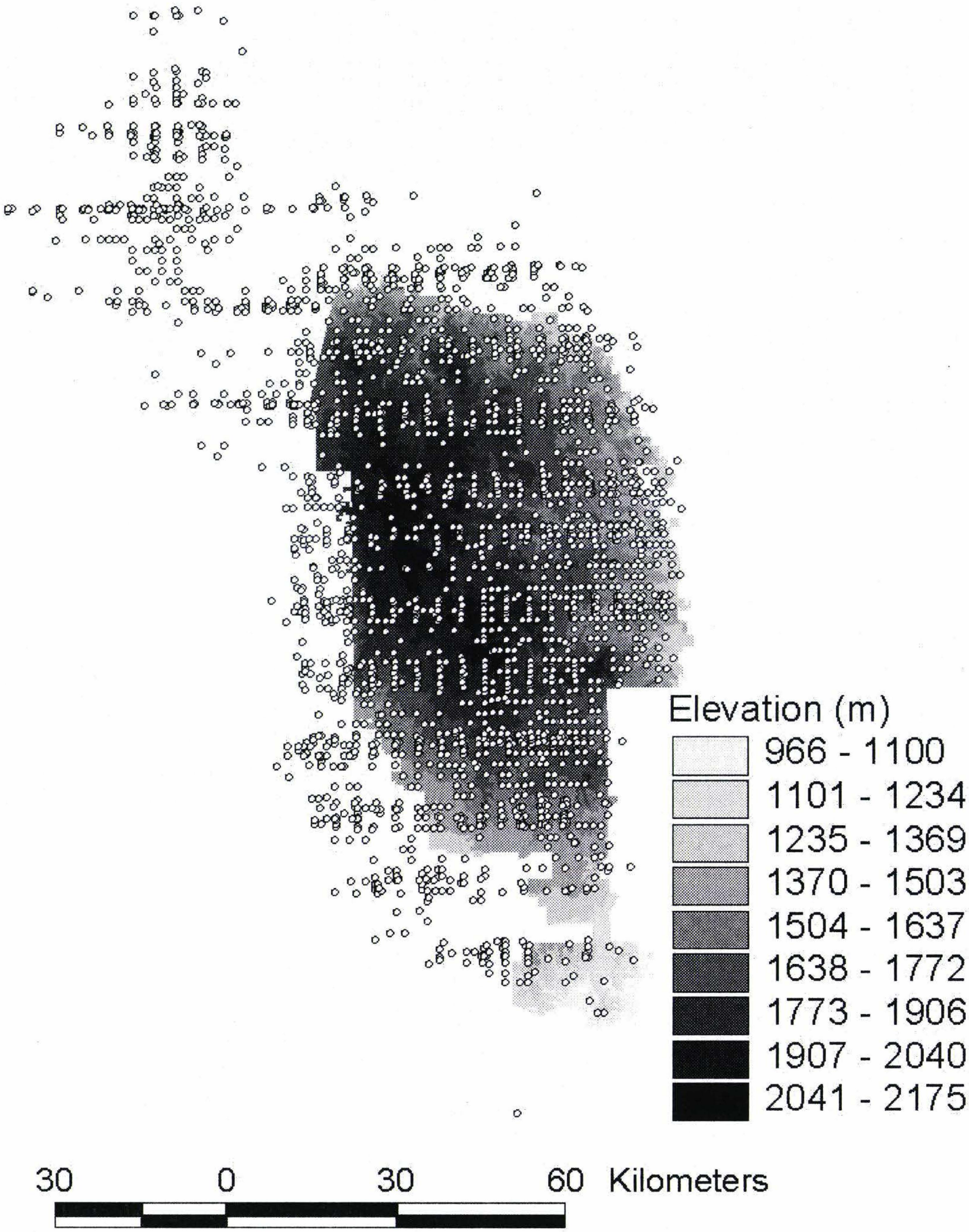

Figure 2. Location of all fires in and around the Black Hills National Forest during the years 1970-2003 overlaid on a digital elevation model of the forest.

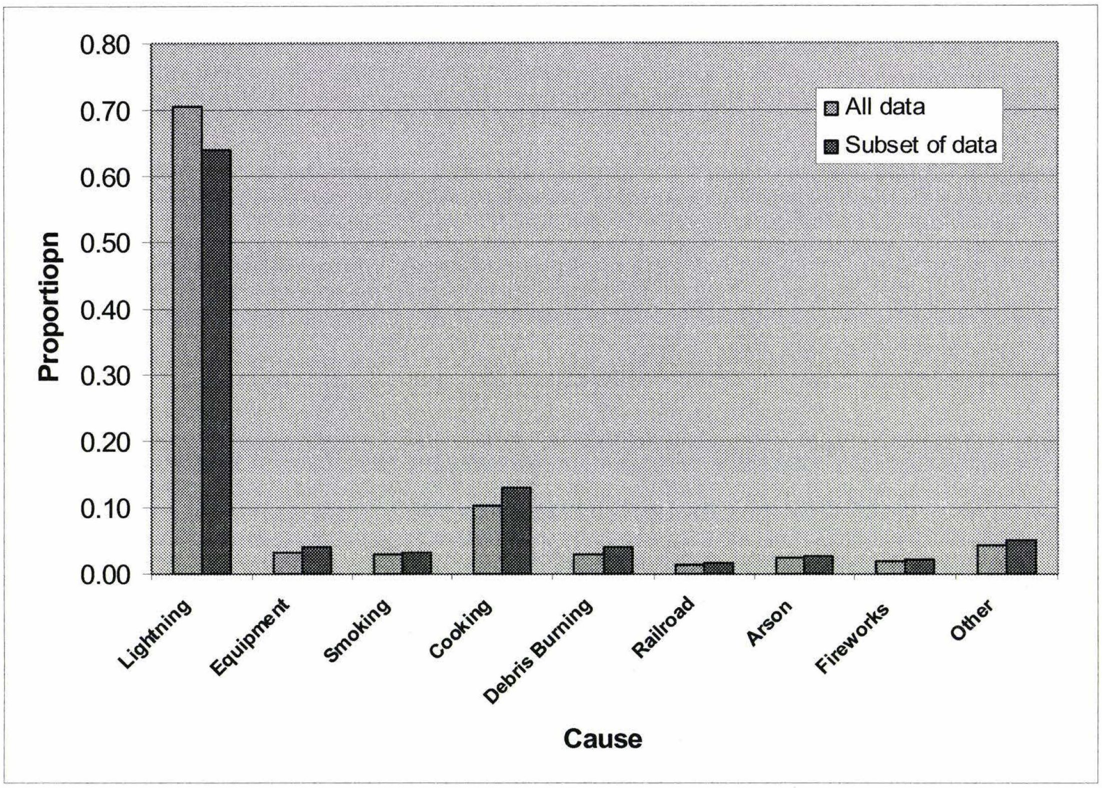

Figure 3. Distribution of fires by causal agent in and around the Black Hills National Forest for the years 1970-2003.

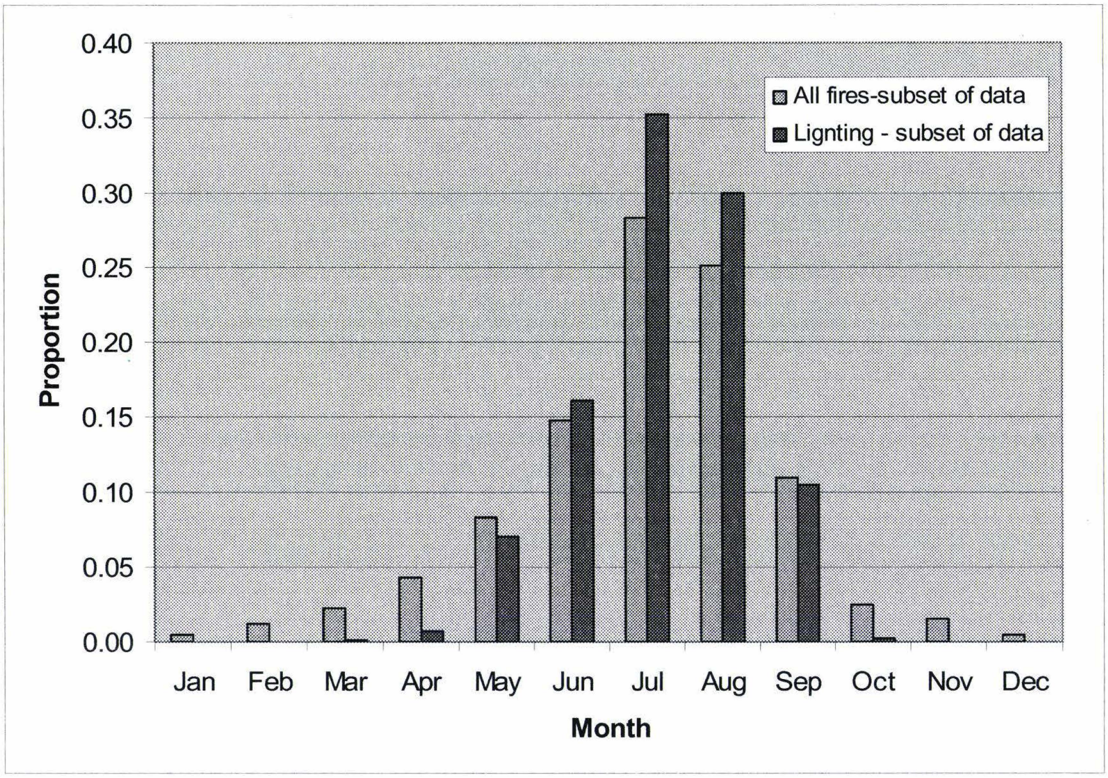

Figure 4. Distribution of fires by month on the Black Hills National Forest for the years 1970-2003.

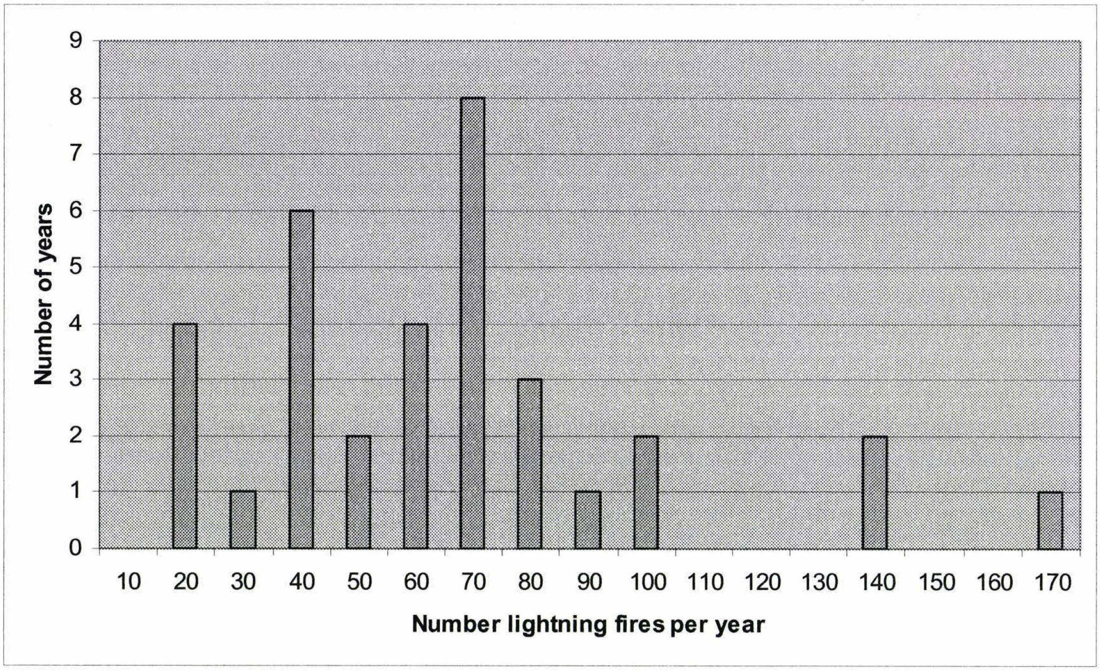

Figure 5. Distribution of the number of years in which a given number of lightning fires were observed on the Black Hills National Forest during the years 1970-2003.

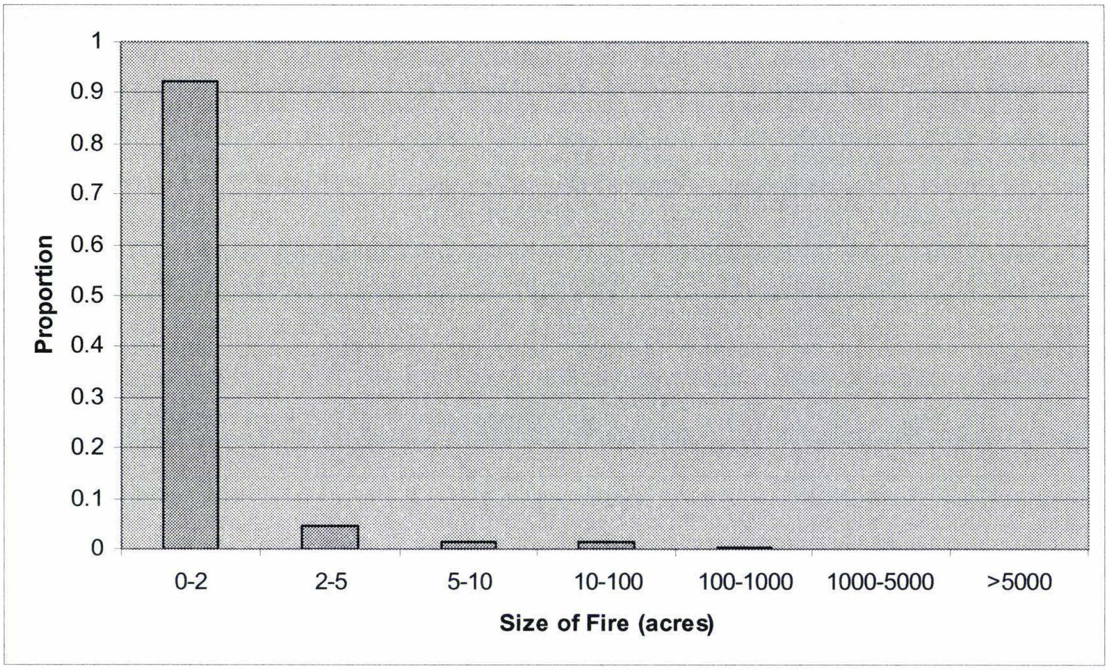

Table 6. Distribution of the size (acres) of lightning fires observed in the Black Hills National Forest during the period 1970-2003.

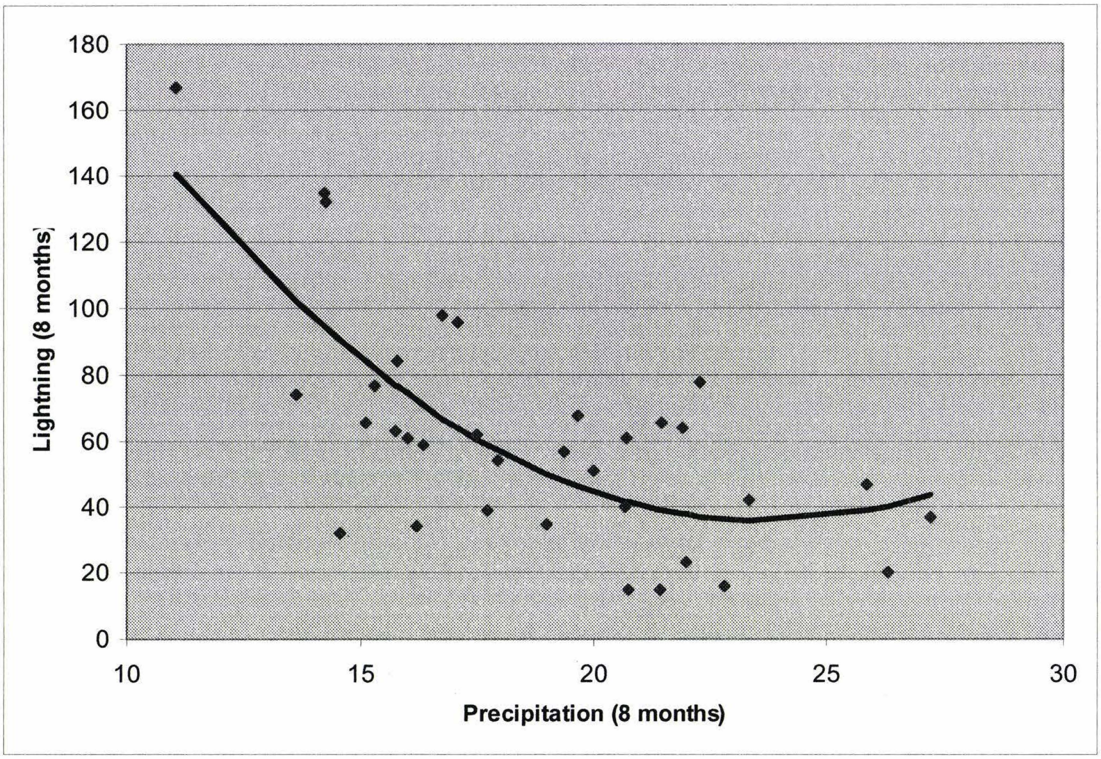

Figure 7. Curve-linear relationship between the total number of lightning fires in a given year as function of the total precipitation (in) during the eight month period from March to October.

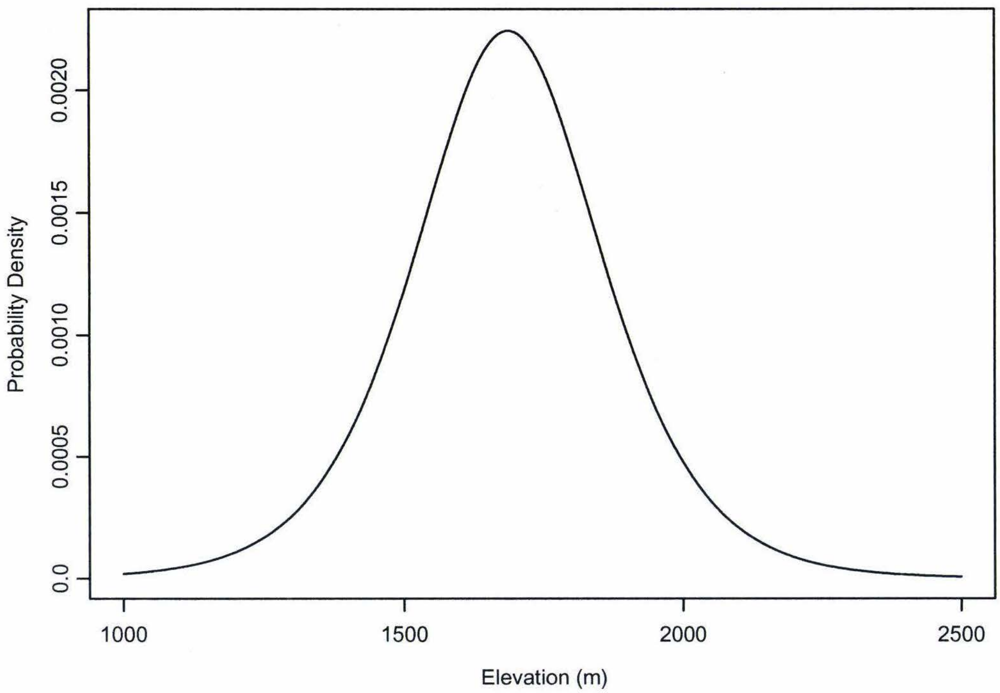

Figure 8. Probability density function of lightning fires as a function of elevation (m).

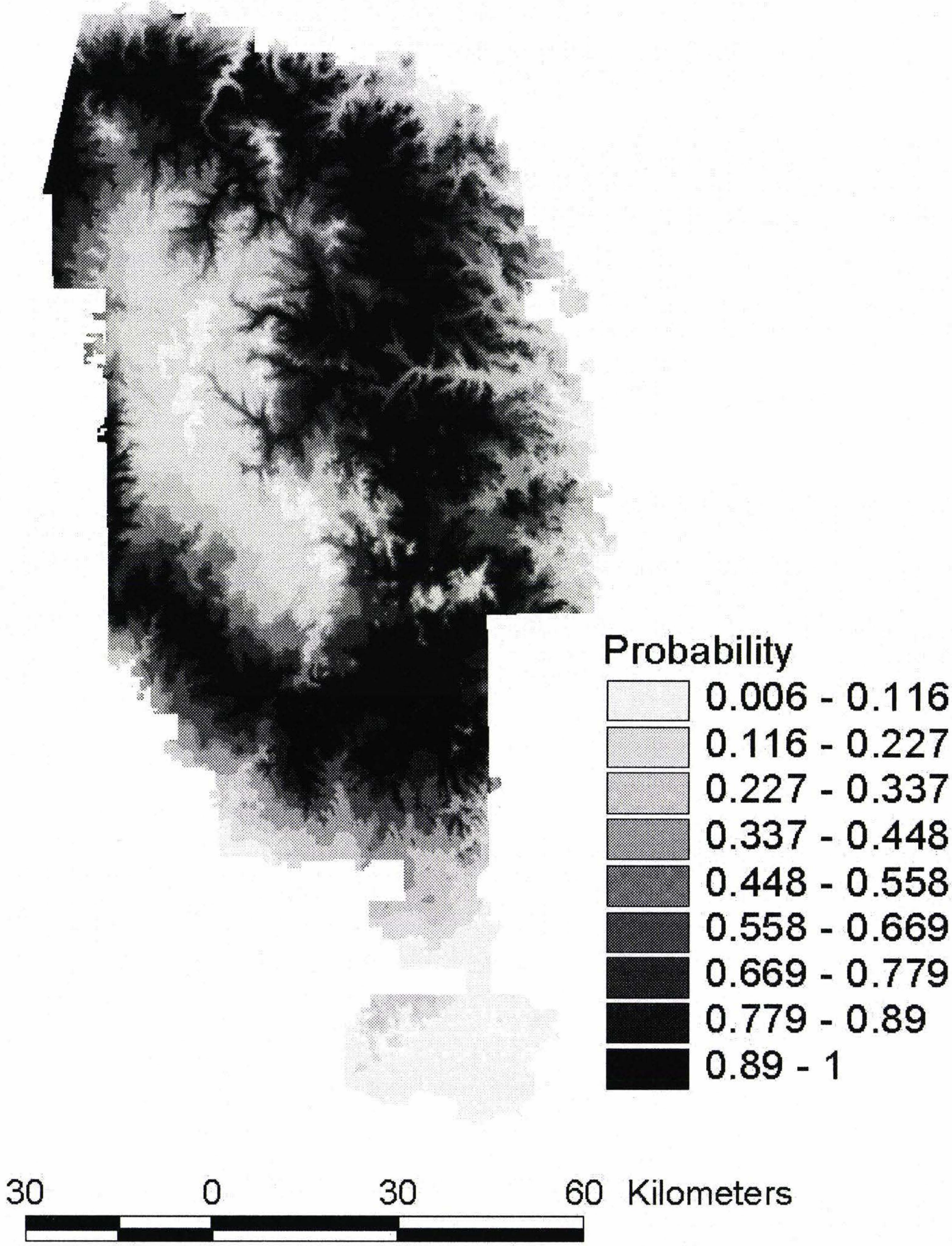

Figure 9. Probability density function of lightning fires as a function of elevation in the Black Hills National Forest. The probability surface has been rescaled so the maximum value is equal to one.

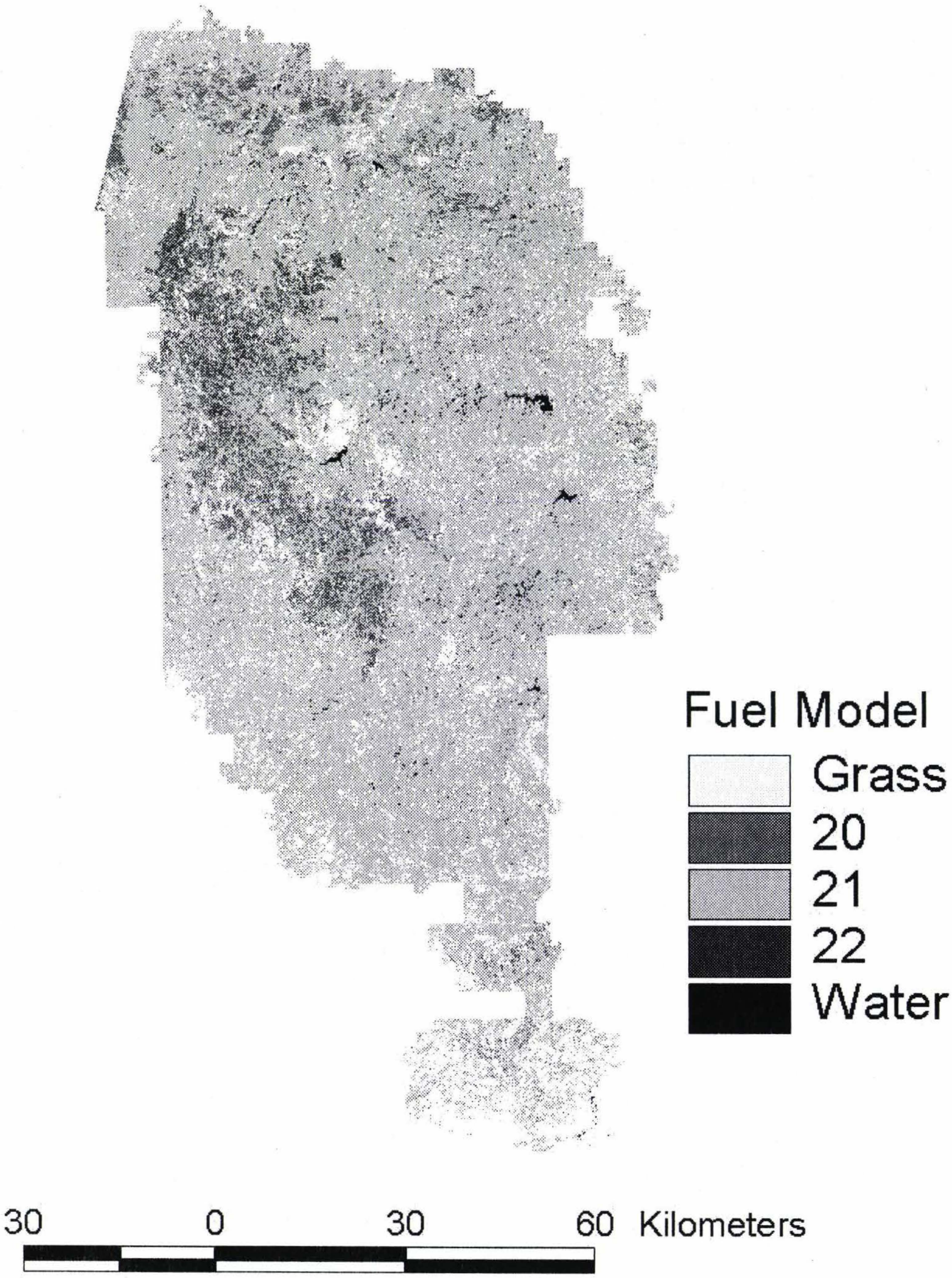

Figure 10. Custom fuel models (classes 20, 21, and 22) developed for the Black Hills National forest using forest fuel inventory data.

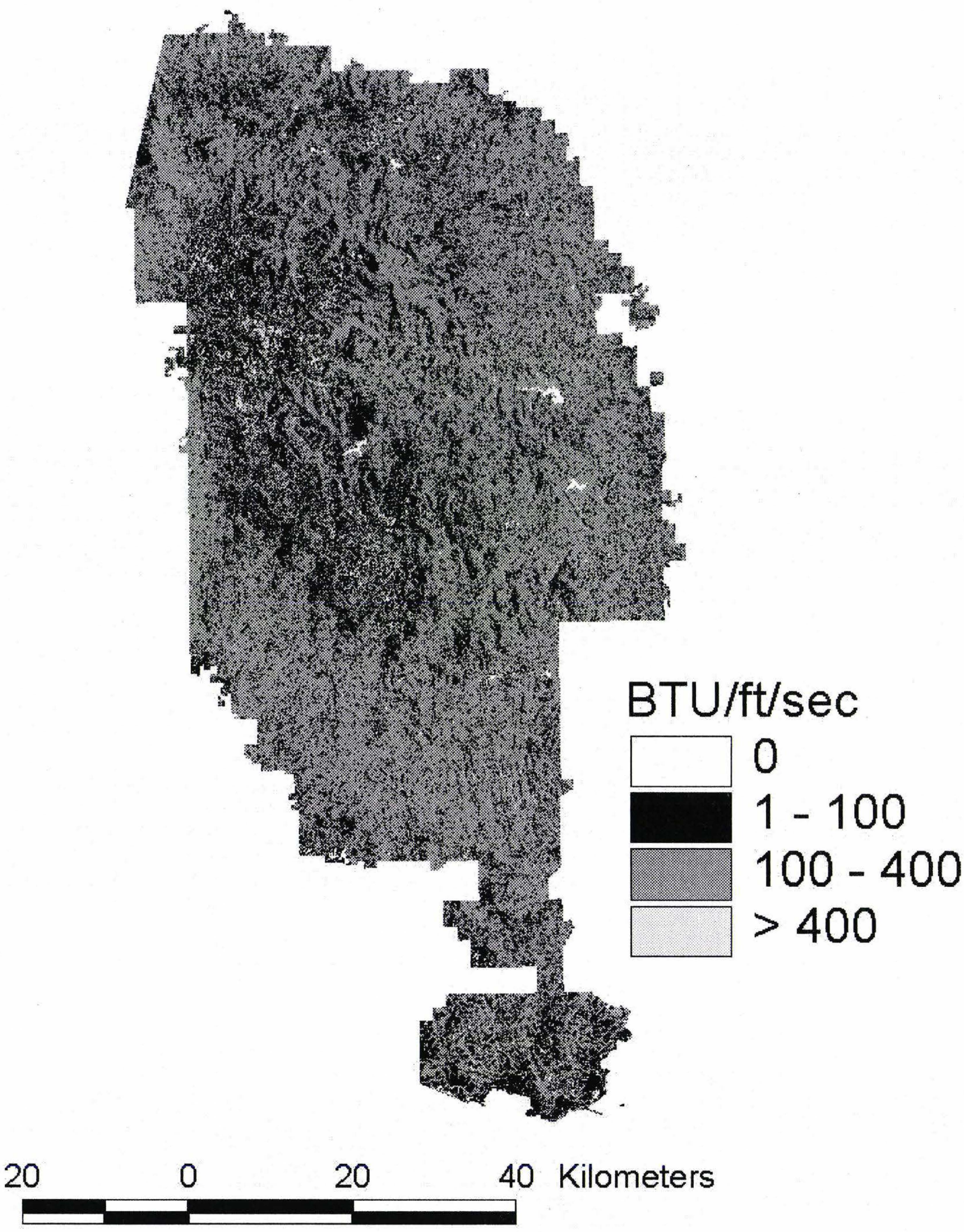

Figure 11. Estimates of the fire line intensity (BTU/ft/sec) based on current fuel loading in the Black Hills National Forest.

Table 1. Sizes of lightning fires simulated in this study.

Number of Pixels	Size Class[1]	Hectares	Acres
7	B	0.4	1
65	C	4.1	10
650	D	40.6	100
3,300	E	206.2	510
6,500	F	406.2	1004
32,500	G	2031.2	5019

[1] Class A = 0 - 0.25 acres; B = 0.25 – 9; C = 10 – 99; D = 100 – 299; E = 300 – 999; F = 1000 – 5000; G = > 5000 (National Forest System)

Table 2. Description of the trend surface models for describing the course-scale variability in forest fuels on the Black Hills National Forest. Circles indicate the inclusion of a variable as a main effect, while shaded cells indicate an interaction between forest classes and topographic and Landsat TM bands. Forest classes were treated as dummy variables with pine being the default forest type. (Published in Reich *et al.* 2004)

Model	Topography[1]			Landsat TM Bands[2]									Forest Class[3]				
	E	S	A	B1	B2	B3	B4	B5	B6L	B6H	B7	B8	P	R	SP	AS	M
Duff (*cm*)	•		•	•		•							•	•			
Litter (*cm*)											•		•				
Fuel Ht. (*cm*)	•												•				
0-0.6 *cm* (*tones/ha*)													•				
0.6-2.5 *cm* (*tones/ha*)													•				
2.5-7.6 *cm* (*tones/ha*)				•									•				
< 7.6 *cm* (*tones/ha*)									•				•				
> 7.6 *cm* (*tones/ha*)		•			•						•		•				

[1] E – elevation, S - slope, A – aspect

[2] B1 – band 1 B2 – band2, B3 - band4, B5 – band5, B6L – band 6 low, B6H – band 6 high, B7 – band 7, B8 - band 8

[3] P – pine, R – riparian, SP – spruce, AS – aspen/deciduous, M – meadows/openings.

Table 3. Variables (circles) used in the binary regression trees to describe the error in the trend surface model of components of forest fuels on the Black Hills National Forest. Forest type was treated as a categorical variable in the regression trees. (Published in Reich *et al.* 2004)

	Topography[1]			Landsat TM Bands [2]									Forest Class [3]				
Model	E	S	A	B1	B2	B3	B4	B5	B6L	B6H	B7	B8	P	R	SP	AS	M
Duff (*cm*)	●	●	●	●			●	●	●	●		●					
Litter (*cm*)	●	●	●			●	●	●	●	●	●						
Fuel Ht. (*cm*)			●	●		●			●	●	●		●	●	●	●	●
0-0.6 *cm* (*tonnes/ha*)	●		●	●	●	●			●	●	●	●	●		●	●	
0.6-2.5 *cm* (*tones/ha*)	●	●	●				●	●	●				●	●	●	●	●
2.5-7.6 *cm* (*tones/ha*)	●	●	●		●	●	●			●		●	●	●	●	●	●
< 7.6 *cm* (*tones/ha*)	●	●	●	●		●	●		●	●	●		●	●	●	●	●
> 7.6 *cm* (*tones/ha*)	●		●	●		●	●		●	●		●	●	●	●	●	●

[1] E – elevation, S - slope, A – aspect
[2] B1 – band 1 B2 – band2, B# - band4, B5 – band5, B6L – band 6 low, B6H – band 6 high, B7 – band 7, B* - band 8
[3] P – pine, R – riparian, SP – spruce, AS – aspen/deciduous, M – meadows/openings.

Table 4. Overall model performance (G-statistic) of the models used to describe the spatial variability of forest fuels on the Black Hills National Forest and Lincoln National Forest. (Published in Reich *et al.* 2004)

Model	Black Hills
Fuel height (*cm*)	0.616
*Litter (*cm*)*	0.612
Duff (*cm*)	0.669
0" – 0.6 *cm* (*tonnes/ha*)	0.548
0.6 – 2.5 *cm* (*tones/ha*)	0.611
2.5 – 7.6 *cm* (*tones/ha*)	0.713
Small (< 7.6 *cm*) (*tonnes/ha*)	0.695
Large (> 7.6 *cm*) (*tonnes/ha*)	0.668

Table 5. Summary statistics of estimation errors of the forest fuels models for the Black Hills National Forest based on the 10-fold cross-validation. (Published in Reich *et al.* 2004)

Statistic [1]	Fuel ht. (*cm*)	Litter (*cm*)	Duff (*cm*)	0-0.6 *cm* (*tonnes/ha*)	0.6-2.5 *cm* (*tonnes/ha*)	2.5-7.6 *cm* (*tonnes/ha*)	< 7.6 *cm* (*tonnes/ha*)	> 7.6 *cm* (*tonens/ha*)
N	151	151	151	151	151	151	151	151
Mean	-0.59	-0.20	0.0	-0.04	-0.56	-3.90	-1.10	-0.27
IQR	6.37	2.19	2.34	0.45	4.77	19.68	20.02	17.04
MAE	6.86	1.90	1.50	0.34	4.68	20.13	18.25	12.71
RMSE	11.40	2.87	1.98	0.51	8.16	36.36	28.56	17.64
SMSE	0.93	1.21	0.86	0.93	1.21	1.40	0.81	0.87
0.95 confidence coverage rate	0.93	0.99	0.95	0.93	0.95	0.90	0.95	0.93

[1] IQR = interquartile range, MAE = mean absolute error, RMSE = root mean square error, SMSE = standardized mean square error.

Table 6. Summary statistics of variables used to identify three groups of forest fuels using a k-means clustering algorithm.

Fuel model	Fuel height (cm)	0 – 0.6 *cm* fuels (*tonnes/ha*)	0.6 – 2.5 *cm* fuels (*tonnes/ha*)	2.5 – 7.6 *cm* fuels (*tonnes/ha*)	Shrub volume (m^3/ha)
20	8.2	0.8	9.4	45.3	24.8
21	4.3	0.3	2,1	6.1	18.4
22	29.0	1.3	24.2	116.7	19.1

Table 7. Summary statistics of fireline intensity (BTU/ft/sec) by fire size and fuels treatment.

Fire Size (Number of Pixels)	Minimum	Mean	Maximum	Average Variance
		0% Reduction		
7	118	154	187	2200
65	74	156	260	3436
650	47	156	422	4472
3300	28	156	617	4498
6500	15	151	718	4562
32500	2	155	1046	4704
		10% Reduction		
7	106	129	154	1758
65	75	127	197	2095
650	43	127	326	2915
3300	38	128	369	3081
6500				
32500	33	128	448	3139
		30% Reduction		
7	62	85	114	1060
65	43	84	170	1498
650	23	84	302	1796
3300	12	83	491	1956
6500	8	84	607	2004
32500	1	85	1008	2210
		50% Reduction		
7	33	50	77	815
65	20	52	148	1924
650	11	50	250	1618
3300	6	52	474	2002
6500	4	52	598	2210
32500	1	53	963	2351
		70% Reduction		
7	14	32	68	2006
65	7	32	135	1826
650	3	33	285	2466
3300	2	31	467	2284
6500	1	31	591	2443
32500	0	31	940	2414